Online Appendices (Not for Publication)

A A Model of the Information Environment and Aggregation

Here we present a simple model of learning based on the Dirichlet sampling process to characterize how information aggregation might arise in a pari-mutuel-style mechanism similar to our IAM. Recall that we partition the set of feasible sales into a set of K ranges or "buckets," denoted by $x_1, \ldots, x_K$. Without loss of generality beyond this discretization, we can characterize the probability that realized sales fall into a given bucket with a K-point multinomial distribution:

$$Y|\pi \in \begin{cases} x_1, & \text{with prob. } \pi_1 \\ x_2, & \text{with prob. } \pi_2 \\ \cdots & \cdots \\ x_K, & \text{with prob. } \pi_K \end{cases} \tag{A.1}$$

In this environment, agents are endeavoring to learn about the entire distribution of sales, as described by the set of unknown parameters $\pi = (\pi_1, \ldots, \pi_K)'$. The fact that agents must learn about an entire probability distribution distinguishes this learning environment from typical univariate learning models in economics. In this environment, agents' evolving beliefs about the unknown probabilities π corresponds to a "distribution over distributions," a modeling environment for which the Dirichlet is particularly well-adapted.

Suppose agents start off with a (common) prior that π follows a Dirichlet distribution with non-negative concentration parameters $\alpha = (\alpha_1, \ldots, \alpha_K)'$, supported on the K-dimensional unit simplex. The prior distribution and expectation for the cell probabilities are denoted:

$$\pi \sim Dir\left(\alpha_1, \ldots, \alpha_K\right), \quad E\left[\pi_k\right] = \frac{\alpha_k}{\sum_{j=1}^{K} \alpha_j} \tag{A.2}$$

Each agent updates her beliefs about π upon observing signals about the likelihood of different states. Specifically, an agent observes m_n signals $s_{n,1}, \ldots, s_{n,m_n}$, drawn independently from a multinomial distribution $MN(\pi)$. From these m_n signals, the agent can compute sample frequencies $\hat{p}_{n,1}, \ldots, \hat{p}_{n,K}$, where $\hat{p}_{n,k} = \frac{1}{m_n} \sum_{j=1}^{m_n} \mathbf{1}\left\{s_{n,j} = k\right\}$, the sample frequency with which the signal falls into the k-th bucket. Given these conjugate distributional assumptions, the posterior distribution for π conditional on these signals will also be Dirichlet:

$$\begin{aligned} \pi | s_n, \alpha &\sim Dir\left(\alpha_1 + m_n \hat{p}_{n,1}, \ldots, \alpha_K + m_n \hat{p}_{n,K}\right) \\ E\left[\pi_k | s_n, \alpha\right] &= \frac{\alpha_k + m_n \hat{p}_{n,k}}{m_n + \sum_{j=1}^{K} \alpha_j} \equiv \tilde{p}_{n,k} \end{aligned} \tag{A.3}$$

In this setting, we want to characterize precisely what information aggregation means in terms of the underlying distribution of sales Y based on all agents' information. Adding the simplifying assumption that the signals are independent across agents, let $M = \sum_{n=1}^{N} m_n$ denote the total number of signals and $\hat{p}_k = \frac{1}{M} \sum_{n=1}^{N} \sum_{j=1}^{m_n} \mathbf{1}\left\{s_{n,j} = k\right\}$ be the proportion of all signals in bucket k. By conjugacy, the aggregated posterior distribution across all N agents will again be Dirichlet:

$$\begin{aligned} \pi | s_1, \ldots, s_N, \alpha &\sim Dir\left(\alpha_1 + \sum_{n=1}^{N} m_n \hat{p}_{1,n}, \ldots, \alpha_K + \sum_{n=1}^{N} m_n \hat{p}_{K,n}\right) \\ E\left[\pi_k | s_1, \ldots, s_N, \alpha\right] &= \frac{\alpha_k + \sum_{n=1}^{N} m_n \hat{p}_{n,k}}{M + \sum_{j=1}^{K} \alpha_j} \equiv \tilde{p}_k \end{aligned} \tag{A.4}$$

This last posterior distribution, $p\left(\pi | s_1, \ldots, s_N, \alpha\right)$, represents the fully aggregated information regarding the distribution of the outcome variable Y available to participants. Intuitively, each individual's draws from the multinomial distribution correspond to m_n "bits" of information about the true distribution for Y and the Dirichlet distribution provides a convenient summary of the total information revealed to individuals.

Note that the posterior beliefs still allow for aggregate uncertainty in the cell probabilities themselves to persist in the populations' information set. That is, while the expected cell probabilities are fixed, the realized cell probabilities remain random with a positive variance. Nonetheless, these expected cell probabilities represent all the information available about the uncertainty in how realized sales will turn out as opposed to a principle that rests on the possibility that no uncertainty exists. This allows us to define "successful" information aggregation in the mechanism in expectation as:

Definition 1 (Information Aggregation in Expectation)**.** We say the IAM aggregates information in expectation if the expected cell probabilities are proportional to the allocation of tickets within the IAM.

Given a large number of independent signals, so that $M \to \infty$, either because each agent receives a lot of information (m_n becomes large) or many agents receive information (N becomes large), the law of large numbers ensures that full-information posteriors converge to the true probabilities:

$$\tilde{p}_k = \frac{\alpha_k + \sum_{n=1}^{N} m_n \hat{p}_{n,k}}{M + \sum_{j=1}^{K} \alpha_j} \to \pi_k, \quad k = 1, \ldots, K. \tag{A.5}$$

This allows us to define what "exactly successful" information aggregation means as:

Definition 2 (Exact Information Aggregation)**.** We say the IAM aggregates information exactly if the true unobserved cell probabilities, conditional on available information, are proportional to the allocation of tickets within the IAM.

These two definitions contrast the aggregate uncertainty in outcomes, characterized by the cell probabilities π, and the aggregate uncertainty in the distribution over outcomes, characterized by the Dirichlet posterior distribution. Clearly, as these definitions do not explicitly rely on the Dirichlet structure, they can be readily interpreted as applying to any measurable setting.

A.1 Incentives for Information Revelation

Given our definitions above, we now examine how incentives might guide individual behavior to reveal their posterior beliefs in the IAM. Suppose the IAM at time t is in a state where each bucket x_k has $\eta_k^{(t)}$ tickets in it and denote the state vector of tickets across buckets by $\eta^{(t)}$. Denote agent n's interim posterior expected beliefs at time t, conditional on the IAM state and history up to t, by $p_n^{(t)} = \left[p_{n,1}^{(t)}, \ldots, p_{n,K}^{(t)}\right]'$. For a risk-neutral agent who has not yet placed any tickets, the marginal value of placing an additional ticket in bucket x_k is simply their posterior expectation of the realized outcome falling in that bucket divided by the number of tickets within the bucket:

$$V_n^{(t)}\left(x_k \middle| s_n, \eta^{(t)}\right) = \frac{p_{n,k}^{(t)}}{1 + \eta_k^{(t)}}$$

In this case, the agent would maximize their payoff by placing their marginal ticket in the bucket that has the highest "odds" – that is, the largest posterior likelihood $p_{n,k}$ relative to the number of tickets that would be placed in the bucket $(1 + \eta_k^{(t)})$. As this discussion makes clear, an agent who places tickets strategically primarily cares not about what the most likely outcome is, but rather the outcome for which the distribution implied by the IAM state differs most from his interim posterior. The most likely outcome is only preferred when a player's beliefs are consistent with the consensus, so that $p_{n,k}^{(t)} \propto \eta_k^{(t)}$, in which case the player has a slight preference for placing tickets in the bucket with highest probability. This preference slightly distorts incentives because of the finite number of tickets placed in the IAM, which results in agents evaluating incentives according to the number of tickets in the bin "plus one." This effect could induce a slight reverse-favorite longshot bias, but since this distortion clearly becomes negligible as the number of tickets grows.

If agent n has already placed $\nu_{n,k}$ tickets in bucket x_k, then the marginal expected payoff from placing an additional ticket in this bucket is:

$$V_n\left(x_k|\nu_n, s_n, \eta\right) = p_{n,k}\left(\frac{1+\nu_{n,k}}{1+\eta_k} - \frac{\nu_{n,k}}{\eta_k}\right)$$

which may also be distorted by the player's existing holdings, particularly if $\nu_{n,k}/\eta_k$ is large (i.e., if player n has placed a large share of the tickets in bucket k). However, in markets where information is spread diffusely across players, $\nu_{n,k}/\eta_k$ would be small and this distortion becomes negligible.

Note that incentives in the IAM are structured so that participants gain nothing from misrepresenting their beliefs. This feature presents an important element of the IAM's design that distinguishes it from continuous double auctions and facilitates its objective of aggregating information. When players disagree about the likelihood of events, the placement of tickets within the IAM ebbs and flows until a consensus forms. The IAM provides an intuitive and accessible mechanism for participants to communicate their beliefs quickly and efficiently. As long as two players disagree, they will be able to express that disagreement by placing more tickets. As this dynamic highlights the disagreement, players update their beliefs until they converge on a consensus distribution over states implied by the IAM.

Result 1 (Incentive Compatibility of Reporting Information in the IAM)**.**
Incentives in the IAM encourage participants to place tickets in the bins for which they most disagree with the probabilities implied by the distribution of tickets already placed within the IAM.

A.2 Information Aggregation as an Equilibrium Property

The incentives identified in the previous section indicate that subjects are encouraged to place tickets in a manner that most expresses their disagreement with the state of the IAM. We now consider how those incentives interact with the nature of equilibrium in the IAM. Suppose all information in the system is publicly revealed, so that every participant in the IAM agrees that the posterior distribution for π is given by equation (A.4). Given a common prior and common knowledge of rationality, the result from Aumnn (1976) stipulates this sort of agreement would be a necessary feature for any equilibrium in the mechanism. This property allows us to abstract from the complications induced by strategic communication and the Folk theorem for dynamic settings, providing a clear and tractable perspective on the possibility of informative equilibria in the IAM in settings with rational expectations.

In this environment, an obvious symmetric Nash equilbrium exists, namely one where individuals place their tickets proportionally to the jointly agreed upon posterior expected cell probabilities, $\nu_{n,k} \propto \tilde{p}_k, \forall n, k$. In fact, this equilibrium is the unique symmetric, simultaneous equilibrium in the IAM, which we establish in the next Proposition.

Proposition 1. *[Information Aggregation as an Equilibrium Property]*

- *Suppose the information aggregation environment is characterized by the distributional assumptions embedded in equations A.1 - A.5. Suppose further that all private signals are publicly revealed, so that* $\tilde{p}_{n,k} = \tilde{p}_k = E\left[\pi_k | s_1, \ldots, s_n, \alpha\right], \forall n, k$

- *Suppose tickets are infinitely divisible and each player places their tickets proportionally to the posterior expected cell probabilities, so that* $\nu_{n,k} \propto \tilde{p}_k, \forall n, k$.

This behavioral strategy represents the unique symmetric equilibrium outcome with agreement, under which the IAM aggregates information in expectation. Further, as information accumulates and $M \to \infty$, *then* $\tilde{p}_k \to \pi_k$ *and the IAM aggregates information exactly in this* *equilibrium.*

The proof of this proposition is given at the end of this section. Proposition 1 indicates that, if private information can be effectively communicated, the IAM's incentives will lead to information aggregation through equilibrium once agreement obtains. Further, the IAM stabilizes in a state where it aggregates information, in the sense that players do not have an incentive to disrupt the IAM. Since the conditions assumed here are essentially equivalent to the definition of an ex-post equilibrium, the result should not be terribly surprising. However, it highlights the simple link between rational expectations, the IAM's incentives, and information aggregation.

Result 2 (Symmetric Equilibrium with Agreement Supports Information Aggregation)**.** *Information aggregation within the IAM can be supported as a unique, symmetric Nash equilibrium.*

The main challenge in establishing information aggregation as a necessary property of equilibrium lies in the complexity of dynamic behavior and determining beliefs off the equilibrium path. Given the dynamic nature of the IAM and the complexity of beliefs and strategies, we'd expect a multiplicity of potentially exotic and asymmetric equilibria that we could not hope to characterize completely. That said, the purpose of our analysis is not to provide an exhaustive characterization of all equilibria in the IAM nor do we intend to relate these equilibria to properties of mechanisms typically associated with prediction and financial markets. Rather, our analysis is restricted to motivating the expectation that Intel's experience in implementing the IAM can inform other complex organizations designing systems to address information aggregation problems. To this end, though the equilibrium analysis above is incomplete, we do establish the possibility of information aggregation and characterize the incentives by which it presents a natural outcome of the IAM.

We conclude this section with a remark on the role of robust theoretical foundations for information aggregation in our application. The mechanism design literature has a rich tradition of mechanisms in which information aggregates in the unique equilibrium satisfying individual rationality and incentive compatibility constraints. Despite the robustness of these devices' theoretical properties, their implementation in complex settings is constrained by their complexity as well as their lack of familiarity to mechanism participants. More complex mechanisms have yet to pass through the crucible of experimental validation by which the rules and incentives of the IAM have been refined and, in so doing, these mechanisms will almost certainly require practical refinements as a result. The pari-mutuel incentives and dynamic elements of the IAM may complicate a complete characterization of its equilibria, but they do present established institutions that facilitate participant interactions. This feature is not exclusively a consequence of theoretical intuition, but relies critically on the experimental foundations for the IAM's design.

A.3 Proof of Proposition 1

Part 1: Best Response Along Equilibrium Path

Given expected cell probabilities and other players' ticket placements, it is optimal for a player to place tickets according to the expected cell probabilities. This partial-equilibrium result establishes that the above assumptions suffice for $\nu_{n,k} \propto \tilde{p}_k, \forall n, k$, to be a best response.

Consider the decision problem faced by the n-th player, conditioning on the players' beliefs $\tilde{p}_n, k = \tilde{p}_k$ and the assumption that all other players are placing their tickets proportionally to the aggregate posterior beliefs. Player n's payoff from any ticket allocation is:

$$E\left[u_n\left(\nu\right)|s_1,\ldots,s_N,\alpha\right] = \sum_{k=1}^{K} \frac{\nu_{n,k}}{\left(N-1\right)\tilde{p}_k + \nu_{n,k}} E\left[\pi_k|s_1,\ldots,s_N,\alpha\right] = \sum_{k=1}^{K} \frac{\nu_{n,k}}{\left(N-1\right)\tilde{p}_k + \nu_{n,k}} \tilde{p}_k$$

Taking first order conditions of the Lagrangian that incorporates a shadow cost (λ) for the constraint that tickets be fully allocated:

$$\frac{\partial}{\partial \nu_{n,k}} E\left[u_n\left(\nu\right)|s_1,\ldots,s_N,\alpha\right] = \frac{\left(N-1\right)\tilde{p}_k^2}{\left(\left(N-1\right)\tilde{p}_k+\nu_{n,k}\right)^2} - \lambda = 0$$

$$\sum_{k=1}^{K} \nu_{n,k} = 1$$

The budget constraint enforces these first order conditions to balance across each of the K cells, so player n's utility maximizing strategy accords with the equilibrium prediction that the players allocate tickets according to the posterior expected cell probabilities.

$$\frac{\left(N-1\right)\tilde{p}_k^2}{\left(\left(N-1\right)\tilde{p}_k+\nu_{n,k}\right)^2} = \frac{\left(N-1\right)\tilde{p}_j^2}{\left(\left(N-1\right)\tilde{p}_j+\nu_{n,j}\right)^2} \implies \frac{\nu_{n,k}}{\nu_{n,j}} = \frac{\tilde{p}_k}{\tilde{p}_j}$$

Part 2: Uniqueness of Equilibrium Outcome

We now establish uniqueness of the equilibrium outcome. First, we show that at least one player has a profitable deviation if the IAM's distribution of tickets is not proportional to the agreed-upon posterior odds. Second, we show that asymmetric ticket allocations are not supportable with agreement.

(a) Suppose the IAM's distribution of tickets is not proportional to $\tilde{p}$, then at least one player has a profitable deviation.

Without loss of generality, suppose $\tilde{p}_1 > \eta_1$ and order the indices so that $\frac{\tilde{p}_1}{\eta_1} \geq \frac{\tilde{p}_2}{\eta_2} \geq \cdots \geq \frac{\tilde{p}_K}{\eta_K}$. Choose as player 1 a subject that weakly underallocates tickets to bucket 1, so that $\nu_{1,1} \leq \eta_1 < \tilde{p}_1$ and select bucket k so that $\nu_{1,k} \geq \eta_k$. Consider the gains and losses to player

1 from shifting ϵ tickets from bucket k to bucket 1.

$$\begin{aligned}\text{Gains from Increasing } \nu_{1,1}: &\quad \left(\tfrac{\nu_{1,1}+\epsilon}{N\eta_1+\epsilon} - \tfrac{\nu_{1,1}}{N\eta_1}\right)\tilde{p}_1 = \tfrac{N\eta_1-\nu_{1,1}}{N\eta_1+\epsilon}\tfrac{\tilde{p}_1}{\eta_1}\tfrac{\epsilon}{N}\\ \text{Cost of Decreasing } \nu_{1,k}: &\quad \left(\tfrac{\nu_{1,k}-\epsilon}{N\eta_k-\epsilon} - \tfrac{\nu_{1,k}}{N\eta_k}\right)\tilde{p}_k = \tfrac{N\eta_k-\nu_{1,k}}{N\eta_k-\epsilon}\tfrac{\tilde{p}_k}{\eta_k}\tfrac{\epsilon}{N}\end{aligned}$$

We want to show that this deviation is profitable for some $\epsilon > 0$, for which it will be sufficient to show:

$$\frac{N\eta_1 - \nu_{1,1}}{N\eta_1}\frac{\tilde{p}_1}{\eta_1} = \left(1 - \frac{\nu_{1,1}}{N\eta_1}\right)\frac{\tilde{p}_1}{\eta_1} > \left(1 - \frac{\nu_{1,k}}{N\eta_k}\right)\frac{\tilde{p}_k}{\eta_k} = \frac{N\eta_k - \nu_{1,k}}{N\eta_k}\frac{\tilde{p}_k}{\eta_k}$$

This inequality holds by the assumptions of our construction:

$$\frac{\tilde{p}_1}{\eta_1} - \frac{\tilde{p}_k}{\eta_k} \geq \underbrace{\frac{\tilde{\nu}_{1,1}}{\eta_1}}_{\leq 1}\frac{\tilde{p}_1}{\eta_1} - \underbrace{\frac{\tilde{\nu}_{1,k}}{\eta_k}}_{\geq 1}\frac{\tilde{p}_1}{\eta_1}\frac{\tilde{p}_k}{\eta_k} \implies \frac{\tilde{p}_1}{\eta_1} - \frac{\tilde{p}_k}{\eta_k} > \frac{1}{N}\left(\frac{\tilde{\nu}_{1,1}}{\eta_1}\frac{\tilde{p}_1}{\eta_1} - \frac{\tilde{\nu}_{1,k}}{\eta_k}\frac{\tilde{p}_k}{\eta_k}\right)$$

(b) Suppose the IAM's distribution of tickets is proportional to $\tilde{p}$, so that $\frac{\tilde{p}_1}{\eta_1} = \frac{\tilde{p}_2}{\eta_2} = \cdots = \frac{\tilde{p}_K}{\eta_K}$, but two players are not playing the same strategy. At least one player has a profitable deviation.

Suppose player 1's allocation differs from the IAM odds. Let $\nu_{1,1} = \eta_1 - \xi$, $\nu_{1,2} = \eta_2 + \xi$, and consider the gains and losses to player 1 from shifting $\epsilon = \xi/N$ tickets from bucket 2 to bucket 1.

$$\begin{aligned}\text{Gains from Increasing } \nu_{1,1}: &\quad \tfrac{N\eta_1-\nu_{1,1}}{N\eta_1+\epsilon}\tfrac{\epsilon}{N}\\ \text{Cost of Decreasing } \nu_{1,2}: &\quad \tfrac{N\eta_2-\nu_{1,2}}{N\eta_2-\epsilon}\tfrac{\epsilon}{N}\end{aligned}$$

We will show this deviation is profitable by verifying that:

$$\frac{N\eta_1 - \nu_{1,1}}{N\eta_1 + \epsilon} > \frac{N\eta_2 - \nu_{1,2}}{N\eta_2 - \epsilon}$$

This inequality can be established by direct substitution:

$$\tfrac{N\eta_1-\nu_{1,1}}{N\eta_1+\epsilon} = \tfrac{(N-1)\eta_1+\xi}{N\eta_1+\xi/N}; \quad \tfrac{N\eta_2-\nu_{1,2}}{N\eta_2-\epsilon} = \tfrac{(N-1)\eta_2-\xi}{N\eta_1-\xi/N}$$

Then:

$$\frac{(N-1)\,\eta_1+\xi}{(N-1)\,\eta_2-\xi} > \frac{N\eta_1+\xi}{N\eta_2-\xi} > \frac{N\eta_1+\xi/N}{N\eta_2-\xi/N} \implies \frac{N\eta_1-\nu_{1,1}}{N\eta_1+\epsilon} > \frac{(N-1)\,\eta_2-\xi}{N\eta_1-\xi/N}$$

Part 3: Information Aggregation Properties

By the agreement assumption and the results of Parts (1) and (2), the IAM ticket allocation represents rational expectations for $E\left[\pi|s_1,\ldots,s_N,\alpha\right]$. Clearly, if every player places tickets proportionally to $\tilde{p}$, then the aggregated distribution of tickets in the IAM will match this distribution. If information accumulates with either a large number of players or with players' signal counts, so that a Law of Large Numbers applies, the IAM would aggregate information exactly.

References

[1] Aumann, R., 1976, "Agreeing to Disagree." *The Annals of Statistics* 4, 6, 1236-1239.

B Forecast Evaluation for Other Predictive Measures from the IAM

This appendix replicates the forecast evaluation results from the main body of the paper using the Median and Mode from the IAM in place of the Mean of the IAM's Distribution.

Table B.1: Summary Statistics for Forecast Data

This table presents summary statistics characterizing the average and standard deviation of unit sales, the target variable to be forecast, and the Median and the Mode of the IAM Distribution. The columns report results broken down by the forecast horizon at which forecasts are generated and the channel through which the sales were delivered.

	Full	Forecast Horizon				Sales Channel	
	Sample	Last Mth	1-3 Mth	4-6 Mth	7-9 Mth	Indirect	Direct
First Period	200602	200602	200602	200603	200604	200604	200602
Last Period	201303	201303	201303	201303	201303	201104	201303
Num of Obs	979	113	339	328	312	339	640
Num of Qtrs	30	30	30	29	28	21	30
Average Sales	1.00	0.97	0.97	1.00	1.03	1.00	1.00
Std Dev Sales	1.00	1.02	1.01	1.00	0.98	1.00	1.00
Average Median	1.16	0.96	1.01	1.16	1.34	1.11	1.19
Std Dev Median	1.01	1.02	1.00	1.01	0.98	0.86	1.08
Median RMSE	0.88	0.27	0.55	0.89	1.12	1.08	0.75
Average IAM Mode	1.15	0.97	1.01	1.13	1.33	1.09	1.18
Std Dev IAM Mode	1.01	1.01	1.01	1.01	0.98	0.88	1.07
IAM Mode RMSE	0.89	0.29	0.57	0.89	1.13	1.10	0.75

Table B.2: Comparing Forecast Loss Across Mechanisms

This table presents Diebold-Mariano tests comparing the point forecasts from the official forecast and the median and mode information aggregation mechanism forecast. The Root Mean Δ Square Error reports the square root of the absolute average difference in the square error for the official and IAM forecasts, signed negatively for cases where the official forecast outperforms the IAM. The Outperformance Frequency captures the frequency with which the IAM forecast was more accurate than the official forecast. The DM-Statistic and p-Value report the Diebold-Mariano test statistic and p-Value using three-way clustered standard errors by product, period, and horizon.

Panel A: Median IAM Forecast

	Num of	Freq IAM	Avg Abs Δ	Diebold-Mariano Test	
	Obs	Outperforms	Loss(*100)	t-Statistic	p-Value
Full Sample	979	60%	16.86	(2.53)	1.2%
Forecast Horizon					
1 Mth	113	67%	6.71	(2.46)	1.6%
2-3 Mths	226	58%	15.24	(1.88)	6.1%
4-6 Mths	328	58%	15.77	(2.29)	2.2%
7-9 Mths	312	61%	22.84	(2.40)	1.7%
Sales Channel					
Indirect	339	56%	27.86	(2.27)	2.4%
Direct	640	63%	11.02	(3.62)	0%

Panel B: Mode IAM Forecast

	Num of	Freq IAM	Avg Abs Δ	Diebold-Mariano Test	
	Obs	Outperforms	Loss(*100)	t-Statistic	p-Value
Full Sample	979	59%	15.32	(2.42)	1.6%
Forecast Horizon					
1 Mth	113	61%	5.50	(2.28)	2.4%
2-3 Mths	226	59%	12.88	(1.65)	10%
4-6 Mths	328	58%	15.64	(2.26)	2.4%
7-9 Mths	312	59%	20.31	(1.87)	6.2%
Sales Channel					
Indirect	339	52%	24.69	(1.97)	4.9%
Direct	640	63%	10.36	(5.25)	0%

Table B.3: Forecast Combination Regressions

This table presents estimates from the forecast combination regressions. Panel A uses the full sample of all forecasts and horizons, with Panels B and C reporting results for horizon and product subsamples. The test F(0, 1, 0) tests the hypothesis that $\alpha = 0$, $\omega_{IAM} = 1$, and $\omega_{Official} = 0$, similarly, F(0, 0, 1) tests $\alpha = 0$, $\omega_{IAM} = 0$, and $\omega_{Official} = 1$. The tests F(., 0, 1) and F(., 0, 1) test the analogous restrictions without the zero-intercept restriction. All tests use three-way clustered standard errors by product, period, and horizon.

Panel A: IAM Median Forecast

	Intercept	IAM Median Weight	Official Fcst Weight		F(., 1, 0)	F(., 0, 1)	F(0, 1, 0)	F(0, 0, 1)
Full Sample	0.30	106%	-43%	F-Stat	4.05	43.40	5.86	58.02
Std. Error	(0.14)	(14%)	(14%)	p-Value	0.7%	0%	0.3%	0%
Forecast Horizon								
1 Month	0.07	114%	-18%	F-Stat	2.91	47.78	3.96	66.33
Std. Error	(0.06)	(16%)	(14%)	p-Value	3.8%	0%	2.2%	0%
2-3 Months	0.15	122%	-41%	F-Stat	3.58	28.95	4.73	38.04
Std. Error	(0.08)	(16%)	(16%)	p-Value	1.5%	0%	1%	0%
4-6 Month	0.32	90%	-29%	F-Stat	3.25	7.54	4.87	11.29
Std. Error	(0.13)	(25%)	(28%)	p-Value	2.2%	0%	0.8%	0%
7-9 Month	0.53	98%	-58%	F-Stat	4.35	12.70	5.79	18.21
Std. Error	(0.24)	(31%)	(28%)	p-Value	0.5%	0%	0.3%	0%
Sales Channel								
Indirect	0.65	93%	-56%	F-Stat	5.50	21.23	7.59	30.75
Std. Error	(0.22)	(23%)	(20%)	p-Value	0.1%	0%	0.1%	0%
Direct	0.16	111%	-40%	F-Stat	3.17	36.24	4.60	46.46
Std. Error	(0.1)	(17%)	(15%)	p-Value	2.4%	0%	1%	0%

Panel B: IAM Mode Forecast

	Intercept	IAM Mode Weight	Official Fcst Weight		F(., 1, 0)	F(., 0, 1)	F(0, 1, 0)	F(0, 0, 1)
Full Sample	0.30	72%	-11%	F-Stat	2.66	17.98	3.93	26.93
Std. Error	(0.15)	(14%)	(15%)	p-Value	4.7%	0%	2%	0%
Forecast Horizon								
1 Month	0.04	95%	1%	F-Stat	0.31	52.63	0.44	67.17
Std. Error	(0.06)	(9%)	(9%)	p-Value	81.6%	0%	64.6%	0%
2-3 Months	0.17	96%	-17%	F-Stat	2.28	19.32	3.38	25.69
Std. Error	(0.09)	(20%)	(17%)	p-Value	8.1%	0%	3.6%	0%
4-6 Month	0.33	68%	-7%	F-Stat	3.99	6.39	5.95	9.45
Std. Error	(0.14)	(21%)	(25%)	p-Value	0.8%	0%	0.3%	0%
7-9 Month	0.53	50%	-12%	F-Stat	3.95	7.51	5.15	9.75
Std. Error	(0.24)	(27%)	(27%)	p-Value	0.9%	0%	0.6%	0%
Sales Channel								
Indirect	0.67	69%	-34%	F-Stat	4.90	19.46	6.76	27.60
Std. Error	(0.23)	(21%)	(18%)	p-Value	0.2%	0%	0.1%	0%
Direct	0.17	70%	1%	F-Stat	1.81	27.46	2.21	40.75
Std. Error	(0.12)	(16%)	(11%)	p-Value	14.3%	0%	11%	0%

C Experimental Instructions

<u>Procedure</u>

<u>Step 1: Register</u>

Register yourself in the system database. If you are not in the database the system will force you to register when you try to log into the Real Deal.

Go to (at any time including now) http://xxxx.caltech.edu/xxx
Select "Sign up as a new user". Choose an ID, a password, and enter a number into the "SS Number" field. We are not using real social security numbers – just pick a number with <u>9 digits</u> that you can remember (or write down). Part of a phone number might be a good idea.

Everyone should enter the following information. It will not be used for anything but is required in the stock application we are using.

University = "Company A" and Class = "Company A"
Street = "123 Main Street" City = "Anytown"
State = "CA" Zip = "12345" Country = "USA"
Enter your real e-mail address and phone number. (Enter area code "123" and then your real seven digit Intel phone number.)

<u>Step 2: Practice</u>

Go to the practice page http://xxxx.caltech.edu/Sales-practice/ prior to the Real Deal to become familiar with the forecasting application. Buy tickets for a few different forecasts and observe how the application responds.

<u>Step 3: Get your secure ID</u>

On the day of the Real Deal, ideally a few minutes before the start time, go to the Real Deal location, http://xxxxcaltech.edu/BusinessUnitYearQ#Date/. It will ask you for the user name and password that you used in Step 1. It will then give you your secure ID, which disguises your identity. Click the "Login" button to enter the Real Deal. You will not be able to use the application until the session begins.

<u>Step 4: Participate in the Real Deal</u>

The session will be held on <u>November 7 at 4:00 PM Pacific Time</u>. Be on time – a few minutes early would be wise. The trial will start exactly on time, allowing for clock differences, and move very quickly. It will likely be over in 30 minutes even though it will remain open for an hour.

Panics or problems: e-mail or call Mister X at ###-###-####. He will be working with Caltech to manage the trial and solve any problems.

We will put general announcements (if needed) on the Real Deal screens.

Determining Winners

Four prizes will be awarded for each of the three quarters forecast during the trial – see details below. We will know which forecast is correct once actual Q4 2006 and Q1, Q2 2007 Business Unit Billings are available. Prizes for each quarter will be awarded after the close of that quarter. All tickets in the correct forecast are considered winning tickets and will be entered into a drawing for prizes. After each prize drawing the winning ticket will be put back in the hopper, so each ticket may win more than one prize.

Q4 2006	Q1 2007	Q2 2007
Drawing 1: $100	Drawing 1: $100	Drawing 1: $100
Drawing 2: $100	Drawing 2: $100	Drawing 2: $100
Drawing 3: $50	Drawing 3: $50	Drawing 3: $50
Drawing 4: $50	Drawing 4: $50	Drawing 4: $50

These prizes will be distributed as an employee recognition award in the near term. Alternative payment methods may be developed in the long term.

Privacy

Participants will remain completely anonymous except to the research team at Caltech and to Mister X, the research manager at Company A. No one else participating in the trial will know for certain who is participating, so they certainly will not know which forecasts you choose. The final forecast generated by all participants will be published, but your personal forecast will be held in confidence by the research team. We will award prizes to the winners, but even the winners will not be announced.

We expect that participants will not share information with one another before, during or after the trial. Past research has shown that the best results are achieved when participants do not share information.